ICCK Journal of Software Engineering
http://dx.doi.org/10.62762/JSE.2026.195385

REVIEW ARTICLE

Electroluminescence Imaging–Driven Software Systems for Solar Cell Defect Detection

Rehana Ghulam[1,*], **Muhammad Fahad Amin Ramay**[1], **Aiza Mukhtar**[1], **Kainat**[1], **Saba Farid**[1], **Nikhat Fatima**[2] and **Khaleelullah Syed**[3]

[1] Department of Computer Science, COMSATS University Islamabad, Sahiwal Campus, Sahiwal 57000, Pakistan
[2] Kakatiya University, Hanamkonda, Telangana, India
[3] Department of Computer and Information Technology Services Administration and Management, Hellenic American University, Athens 10680, Greece

Abstract

Electroluminescence imaging is widely used for detecting defects in solar cells. It reveals electrically active damage that remains invisible under conventional optical inspection. Most existing studies apply machine learning models to classify electroluminescence images and report performance mainly through accuracy scores. Inspection is often treated as an isolated prediction task, while physical defect mechanisms, sensing variability, representation bias, decision risk, and deployment constraints receive limited attention. As a result, strong benchmark results may not translate into reliable inspection outcomes in manufacturing environments. This paper presents a conceptual, non-systematic framework that reframes electroluminescence inspection as a layered system rather than an isolated prediction task. The analysis synthesizes existing research through this structured lens to identify recurring blind spots and system level misalignments. The objective is not to conduct a systematic review or empirical benchmarking study, but to provide a conceptual foundation for positioning automated inspection within a broader physical and operational context.

Keywords: electroluminescence imaging, solar cell inspection, defect semantics, automated inspection systems, representation learning, decision-making under uncertainty, photovoltaic quality assurance, system-level analysis.

1 Introduction

Global energy systems are undergoing a transition toward low carbon and renewable sources. Among these, photovoltaic technology plays a central role due to its scalability, declining cost, and wide deployment across utility and distributed settings. The long term performance and economic viability of photovoltaic installations depend not only on energy conversion efficiency but also on the structural and electrical integrity of individual solar cells. Even minor defects introduced during manufacturing can propagate into

Submitted: 07 January 2026
Accepted: 12 March 2026
Published: 22 April 2026

Vol. 2, **No.** 2, 2026.
10.62762/JSE.2026.195385

***Corresponding author:**
Rehana Ghulam
rehanaghulam97@gmail.com

Citation
Ghulam, R., Ramay, M. F. A., Mukhtar, A., Kainat, Farid, S., Fatima, N., & Syed, K. (2026). Electroluminescence Imaging–Driven Software Systems for Solar Cell Defect Detection. *ICCK Journal of Software Engineering*, 2(2), 85–101.

module level degradation, reducing reliability and operational lifespan.

There has been an increase in the need for quality assurance in manufacturing solar cells with the enhancement of photovoltaic (PV) technology. Efficiency losses and lower operational lifetimes can result from even the tiniest of software defects. This is why non-destructive testing techniques are utilized in both industrial and research contexts. One of the most commonly used tools in the industry is Electroluminescence (EL) imaging. With the use of EL imaging, it is possible to actively visualize regions and defects of solar cells with the use of forward bias, which are not visible with ordinary optical inspection. EL images are essential for the analysis of defects of crystalline silicon solar cells. Recently, it has become more common to use deep learning and machine learning techniques to automate this analysis. Numerous studies have utilized this technique and have reported positive outcomes with the use of related architectures and convolutional neural networks in the imaging processes. In the majority of these studies, the focus has been on the detection or classification, and the success has been determined based on accuracy. While this research has been valuable, it has also created other concerns [1, 2].

First, contextual details related to inspection are often obscured by the emphasis on algorithmic performance. Reported results are difficult to compare across studies because image acquisition conditions, defect labeling criteria, and evaluation protocols differ substantially. For example, a model trained on high contrast laboratory images may achieve strong accuracy but perform poorly when applied to images captured under industrial lighting variability.

Second, the physical mechanisms that give rise to defect patterns in electroluminescence images are frequently discussed only briefly. Yet these mechanisms directly influence visual appearance. For instance, a micro crack and a region affected by series resistance may both appear as dark areas, although their electrical causes and long term implications differ. Without linking visual patterns to physical origins, classification categories may oversimplify the defect landscape.

Third, deployment considerations such as reliability, interpretability, and operational constraints are often mentioned at a high level without systematic analysis. A model may achieve high accuracy in offline testing, but inference latency or limited hardware resources in manufacturing environments may prevent real-time use. In such cases, predictive performance alone does not determine practical suitability.

The main goal of this paper is to reframe electroluminescence based solar cell inspection as an integrated multi layer system that connects physical mechanisms, computational modeling, and deployment realities. This paper takes a conceptual and systems approach to the inspection of defects in solar cells via EL. We are constructing a conceptual framework that allocates existing literature to specific functional tiers in an inspection pipeline and discusses the literature to assimilate it within a broader inspection and defect quantification system. The use of literature in this study is selective and analytical rather than exhaustive. The manuscript does not aim to catalogue all prior contributions, nor does it follow predefined inclusion or exclusion criteria associated with systematic review methodology. Instead, published studies are examined as representative examples that illustrate how specific layers of the inspection system have been emphasized or overlooked. The synthesis performed here is conceptual. It reorganizes existing contributions according to their functional position within the proposed framework rather than evaluating them through quantitative aggregation. In this sense, the framework serves as an interpretive lens rather than a review protocol.

We construct a conceptual framework that illustrates the system components for the inspection of defects in solar cells via EL. The framework is constructed as a layered approach, with system-level inspection concepts on the bottom and the other levels being representation learning, decision-making paradigms, deployment, and the inspection of solar cells via EL emerging technology. This layered approach illustrates the relationships to the subsequent system components and the relationships among various systems. The key contributions of this paper include:

1. To begin with, a multi-layered conceptual framework for EL-based solar cell inspection is presented, which includes the physical, sensing, representation, decision, and deployment layers.

2. The second contribution is the discussion of the existing research trends through the framework, which provides the basis for the identification of the predominant assumptions and the blind spots.

3. The third contribution offers several avenues

for future research, focusing on system-level perspectives that tend to be overlooked in most existing research.

The rest of the paper is structured as follows. In Section 2, a conceptual framework is introduced that situates EL-based solar cell inspection in a multi-layered system with physical, computational, and deployment elements. In Section 3, the semantics of defects are discussed, while in Section 4, representation learning is analyzed conceptually. In Section 5, the focus is on the decision-making processes in automated inspection systems. In Section 6, the discussion centers around deployment and the various factors that influence the consideration of inspection systems in industrial settings. In Section 7, the focus is on the recurring blind spots and the evaluation methodologies that have been documented in existing research. In Section 8, future research is discussed from the perspective of a system-level framework. Finally, in Section 9, the key takeaways from the research are summarized, and the paper is concluded.

2 A conceptual framework for EL-based solar cell inspection

Using EL imaging for automated inspections involves far more than just applying a classification model to a dataset. In practice, inspection results can be traced back to a series of interconnected steps from the creation of a physical defect to the manufacturing process. Considering this, a framework is useful for understanding the interactions between the various elements of an EL-based inspection system [3]. The framework in Figure 1 is divided into five functional layers. The physical layer represents the material and electrical defect mechanisms that generate electroluminescence patterns. The sensing layer captures the image acquisition process and sources of variability introduced by hardware and environmental conditions. The representation layer concerns the encoding of image information for computational analysis. The decision layer converts encoded information into inspection outcomes such as defect classification or rejection. The deployment layer reflects operational constraints, including latency, hardware limitations, and integration into manufacturing workflows. These layers are not meant to indicate definitive boundaries of processing, but they assist in structuring the analysis of prior work and assessing the disposition of various challenges [4].

The layers are analytically distinct but operationally

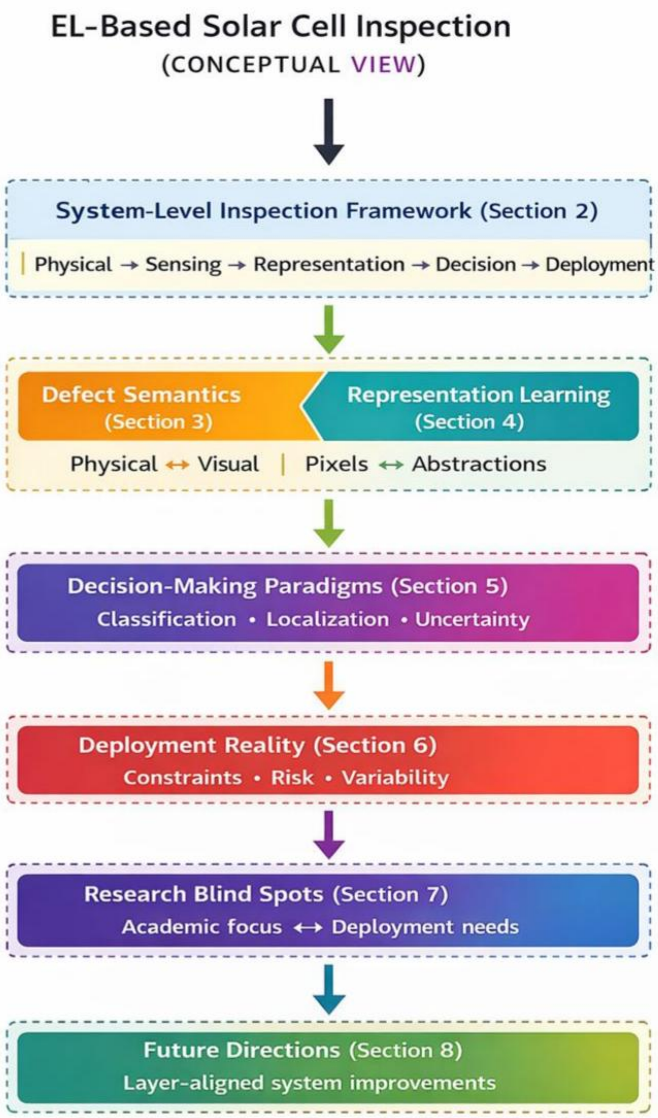

Figure 1. A conceptual overview of the EL-based solar cell inspection pipeline, framing the system-level discussion.

interconnected. The physical layer concerns defect causation independent of imaging hardware. The sensing layer ends once the electroluminescence signal is converted into a digital image. The representation layer begins when computational encoding of that image occurs. The decision layer starts when encoded features are mapped to inspection outcomes. The deployment layer encompasses constraints external to the model, including latency, hardware capacity, and workflow integration. While interactions exist across layers, each layer isolates a specific source of variability for systematic analysis [5, 6].

2.1 Physical layer: Defect mechanisms and el emission

Electroluminescence imaging is based on light emission that occurs when a solar cell is forward biased.

When current flows through the cell, electrons and holes recombine and release energy in the form of light. In a healthy region of the cell, this recombination process is relatively uniform, producing a consistent brightness pattern in the EL image. A physical defect disrupts this process. For example, a micro crack can interrupt the current path, reducing the local flow of charge carriers. As a result, less recombination occurs in that region, and it appears darker in the EL image. Similarly, shunts or regions with increased series resistance alter the local electrical behavior, which changes the intensity of emitted light. The EL image therefore reflects variations in electrical activity caused by underlying material imperfections.

However, some defects cause only small changes in recombination, making them difficult to distinguish from background variation or imaging noise. This places an inherent limit on detectability, independent of the computational model used for analysis.

2.2 Sensing layer: Image Acquisition and Variability

The sensing layer includes capturing and converting EL signals into digital photographs. Several parameters affect digital image quality, like the sensitivity of the camera, the exposure time, the ambient conditions, and the level of image noise. Although these parameters are frequently dealt with as noise, they can severely impact the quality of images for subsequent analysis [7].

The majority of studies document images acquired in well-defined laboratory conditions. While using comparable models in industrial circumstances, the systems are likely to underperform as a result of the augmented variability. Such consequences are important. Instead of considering these consequences as sensing and measuring limitations, they should be considered as ‘deployment conditions mismatched with the assumptions of the sensing system.

2.3 Representation Layer: Encoding information from EL images

The representation layer deals with how the information in the EL images is encoded for automatic analysis. Previous methods focused on hand-crafted features meant to capture some texture or intensity patterns. More recent works have moved on to learned representations using deep neural networks [3]. Learned features are more flexible than hand-crafted features, but they can also create additional problems. Since learned representations can encode features that are artifacts of the particular training set used, which are not related to the actual defects, this can be problematic, especially when the training sets used to train the models are small or homogeneous. Assessing which image regions are being amplified or attenuated at this stage is therefore critical for determining the degree of generalization [8].

2.4 Decision layer: From predictions to inspection outcomes

Judgment modules convert representations into inspection outcomes, including defect types and accept/reject decisions. Various studies use different terms for these activities, ranging from binary classification, multi-class classification, to localization [3]. These options are often related to the availability of datasets and not to the practical needs of the operation. In an industrial setting, it is usually the case that a choice must be made. The costs of false negatives and false positives are not the same, and the level of confidence in a prediction may be as important as its correctness. Thus, the frameworks for decision making must be in line with the goals of the inspection, not just the overall accuracy, to justify the trade-offs being made.

2.5 Deployment layer: Practical integration and use

The last layer in the framework looks more closely at deployment considerations, including inference time, hardware constraints, system maintenance, and interpretability for users. While these factors tend to be mentioned, they are seldom examined in detail.

Table 1. Sources of variability across functional layers of EL-based solar cell inspection systems.

Framework layer	Primary sources of variability	Typical impact on inspection
Physical layer	Material defects, cell aging	Limits defect visibility
Sensing layer	Noise, exposure, camera settings	Inconsistent image quality
Representation layer	Feature bias, dataset homogeneity	Reduced generalization
Decision layer	Threshold selection, class imbalance	Unstable decisions
Deployment layer	Hardware limits, workflow constraints	Performance degradation

Isolating deployment from the other stages helps to explain why some methods are successful in the lab but are problematic in the field [8]. Conceptually, inspection systems cannot be successful unless they align with the actual manufacturing processes and limitations. Table 1 highlights the variability sources across the inspection layers.

At the physical layer, variability arises from material defects and cell aging, which determine the fundamental visibility limits of certain fault types. At the sensing layer, differences in exposure time, camera sensitivity, and ambient conditions can lead to inconsistent image contrast and noise levels. Within the representation layer, dataset homogeneity or biased feature encoding may reduce generalization when systems are exposed to unseen conditions. At the decision layer, threshold selection and class imbalance can produce unstable or risk sensitive outcomes. Finally, at the deployment layer, hardware constraints and workflow integration issues may degrade performance even when predictive accuracy remains high in controlled testing.

When viewed together, the five layers show that the interactions that shape inspection of EL-based solar cells are physical, computational, and operational. If there are improvements at a single stage, it is unlikely that there will be overall system gains if the other layers are not considered. The layered structure is intended to directly respond to the limitations identified in the Introduction. The physical layer restores attention to defect mechanisms that were previously reduced to visual labels. The sensing layer makes acquisition variability explicit rather than treating it as noise. The representation and decision layers separate encoding choices from outcome policies, allowing error asymmetry and uncertainty to be examined independently of accuracy. The deployment layer brings operational constraints into the analytical core of the inspection system instead of leaving them as secondary considerations. Through this structured mapping, the framework mitigates the fragmentation observed in prior research by linking physical causation, computational processing, and industrial feasibility within a single conceptual model.

The framework can be used to analyze prior research by identifying the layer emphasis within each study. For example, studies that report improved classification accuracy through architectural modifications primarily operate within the representation layer. Works focusing on threshold optimization or class imbalance adjustments address the decision layer. Research that evaluates inference speed or hardware feasibility engages the deployment layer. By categorizing contributions in this manner, the framework enables structured comparison across studies that otherwise appear methodologically unrelated. It reveals which layers are extensively explored and which remain underexamined. Figure 2 situates the proposed framework on EL-based inspection within the larger context of manufacturing to delineate the system boundaries of the framework in this paper.

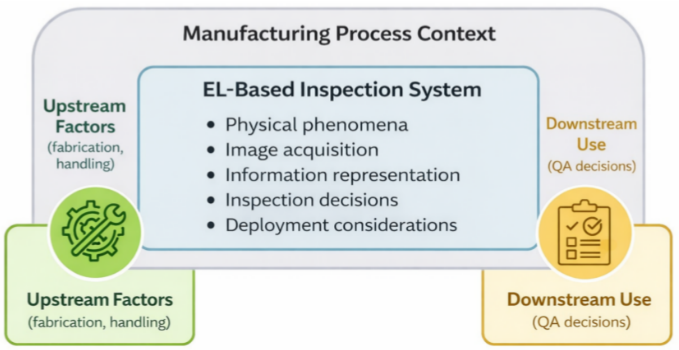

Figure 2. A conceptual overview of the EL-based solar cell inspection pipeline, framing the system-level discussion.

2.6 Distinction from conventional EL inspection pipelines

Conventional EL inspection pipelines typically follow a linear structure. An image is acquired, preprocessed, encoded through a model, and classified into defect categories. The emphasis is placed on improving feature extraction or classification accuracy. These pipelines are effective for benchmarking purposes. However, they often treat sensing variability, physical defect semantics, and deployment constraints as secondary considerations [9].

The proposed framework differs in structure and intent. It does not describe a sequence of processing steps alone. Instead, it separates inspection into analytically distinct layers that correspond to physical causation, signal acquisition, representation encoding, decision policy, and operational integration. This separation enables examination of variability sources that remain implicit in conventional pipelines [10]. An important advantage of this layered approach is diagnostic transparency. When performance degradation occurs, the framework allows the source to be traced to a specific layer, whether physical ambiguity, sensing instability, representation bias, decision threshold asymmetry, or deployment constraint. Conventional pipelines rarely provide this structured attribution.

Another advantage lies in evaluation alignment. Rather than optimizing a single predictive metric, the framework encourages joint consideration of reliability, uncertainty management, and operational feasibility. This broadens the criteria by which inspection systems are assessed.

3 Defect semantics: From physical faults to visual patterns

Within the proposed multi layer framework, defect semantics operates at the interface between the physical layer and the representation and decision layers. Physical mechanisms generate electroluminescence patterns, but these patterns must be interpreted and encoded before a computational decision is made. The meaning assigned to a visual pattern influences both the features extracted during representation learning and the thresholds or class boundaries used in decision making. Defect semantics therefore links physical causation with computational interpretation and directly affects inspection reliability.

Automated analysis of EL images hinges on how defects in matter get converted into patterns that can be visually registered. This conversion is not always easy. Even though EL imaging is important for understanding the electrically active parts of a solar cell, many factors influence the appearance visually. These factors include the mechanisms that produce and sense the images, the representation of the images, and so on. Many of the studies to date define defect types as visually separable, distinct classes. However, the real world often is more complex. Inspecting cells reveals many more gradients than visually distinct patterns for many types of defects. On the one hand, different causes can produce the same visually distinct patterns. On the other hand, the same cell can acquire the same type of defect in many different ways, visually distinct, across several cells, or under different imaging conditions. These factors imply that EL images of defects and defect interpretation lack clarity [8]. A conceptual mapping between physical defect mechanisms in solar cells and their visual manifestations in EL images is presented in Figure 3.

The figure illustrates two conceptual domains. On one side, common physical defect categories such as micro-cracks, shunts, broken contact fingers, and inactive regions are shown. On the other side, their typical visual expressions in electroluminescence images are represented as dark lines, localized spots, band like dim areas, or diffuse low intensity zones.

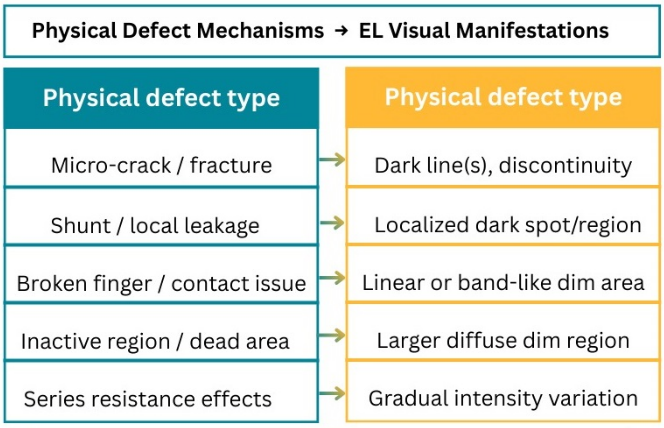

Figure 3. Conceptual mapping between physical defect mechanisms in solar cells and their visual manifestations in EL images.

Arrows between the two domains indicate that the relationship is not strictly one to one. A single physical defect may produce different visual patterns depending on imaging conditions, and similar visual patterns may arise from distinct electrical causes. The mapping therefore emphasizes semantic overlap rather than deterministic correspondence.

3.1 Physical defects and their ELA signatures

EL images portray micro-cracks and other fractures that occur at the microstructural level of the silicon wafer. A micro crack is a small structural fracture in the cell that partially interrupts current flow. When current cannot pass uniformly across the cracked region, that area emits less light and appears as a dark line or segmented feature in the EL image. Shunts refer to unintended low resistance pathways within the cell that allow current to bypass the intended p n junction region. These pathways disturb the normal electrical behavior of the cell and often appear as localized dark spots or patches in EL images. Broken contact fingers are interruptions or degradation in the thin metallic grid lines printed on the cell surface to collect current. When these conductive lines are damaged, current collection becomes uneven, producing band like dim areas across the image.

Defects on broken or degraded contact fingers can lead to the formation of expanded areas that lower the level of emitted light and produce bands. In some cases, these spatial patterns can be confused with those produced by micro-cracks, and this is even more likely to happen when the contrast of the images is low. The presence of these spatial patterns consistently illustrates the micro-cracks and reinforces the importance of adequately contextualizing these images in detailed patterns. Inactive or dead zones in a solar cell may create more diffuse zones of lower intensity. These areas can be easier to identify, but they may be defined poorly.

Increased series resistance, which refers to resistance within the cell materials or contacts that limits current flow, may reduce overall brightness and obscure distinctions between defect types.

3.2 Semantic ambiguity and overlapping visual patterns

The above-stated examples demonstrate that EL defect interpretation is very rarely a case of a one-to-one mapping problem. Rather, this is a case of semantic overlap, where, in particular conditions, several defect mechanisms could result in the same pattern [11].

On the other hand, from a conceptual perspective, the overlap also carries some meaning. Classification labels, which serve as a default ground truth, lead to the disregard of uncertainty; in turn, the omitted uncertainty leads to the performance metrics that are produced reporting an inflated reflex of the reliability of the inspection. Whereas in truth, a model may show an excellent performance and level of accuracy with a selected data set, while in reality, it could be failing in multifaceted environments. However, the class of defects can also be poorly constructed due to semantic ambiguity. Misconstruction can occur due to a multitude of reasons. For instance, a poorly constructed class can result from the boundaries of the class being defined purely by the conventions of the labelling, and with no regard to physical separation. Misconstruction can also lead to an unintentional phenomenon of low complexity models producing inaccurate class predictions, defined within the class boundaries of more complex models. Of course, building a system to inspect the defect types of EL and the systems in control of it with appropriate measures is a more pragmatic and useful approach to this problem, such as a confidence threshold or a reject option. The defect types and their EL manifestations in Table 2 are diverse in terms of the visual ambiguities they represent. Table 2 also shows the automated inspection measures and their implications.

The visual ambiguity levels presented in Table 2 are assigned conceptually rather than quantitatively. A defect category is labeled as having high ambiguity when its visual manifestation frequently overlaps with other defect patterns or when its appearance varies substantially under different imaging conditions. Moderate ambiguity indicates that the defect typically exhibits distinguishable spatial characteristics but may still be confused with related electrical anomalies in low contrast or noisy images. These levels reflect recurring observations reported in the literature and practical inspection experience, rather than statistical measurements derived from a specific dataset.

3.3 Implications for automated inspection systems

There is direct design implications related to understanding defect semantics besides an interpretive exercise. If inspection systems are built with a disregard for semantic uncertainty, they will prioritize reliability over the accuracy of their performance metrics. Conversely, inspection systems that explicitly target overlapping defect patterns will be able to implement more cautious decision strategies. For example, an inspection system could implement a workflow where uncertain defect declarations are not sent for primary analysis, in lieu of automation, to be analyzed by a human. In some circumstances, this would be considered a loss of automation, but in others it will be a gain, particularly in the inspection of uncertain defects. Defect semantics, in a more holistic approach, is about integrating physics and computation. It is telling inspection systems that there is more to the inspection of patterns than surface recognition; inspection systems aim to optimize the pattern recognition of underlying system structures. This is in a chapter with the system-level design framework described in earlier chapters, and explains the lack of progress that comes with model-centric design and the consequent operational gain that is not achieved. This analysis demonstrates that ambiguity in defect meaning propagates forward into both representation encoding and downstream decision policies within the inspection framework.

4 Representation learning in EL-based solar cell inspection

The presence of defects is one thing, and the way visuals are processed before a decision is made is another. Learning a representation is a way to better capture the raw image data and the result of an inspection. While this is a highly technical thing to discuss, it is also a way to think about the defect information in terms of preservation, transformation, or erosion. Focusing on inspection systems and defect detection using EL, representations are a kind of structured content/image encodings that emphasize some features and deemphasize others. The structured representation, or encoding, directly affects the detection abilities and reliability of the inspection systems. Therefore, it is justified to consider representation beyond the classification metrics and the reason for the choice made. Figure 4 illustrates the idea of image abstraction as information reduction across stages of processing. The left side represents a raw electroluminescence image containing detailed spatial variations, noise, and background intensity gradients. The middle stage represents intermediate feature extraction, where certain spatial patterns such as edges or intensity contrasts are emphasized while irrelevant variation is suppressed. The right side represents a compact representation used for decision making, where only selected defect related features remain. The figure does not contrast good versus bad representations directly. Instead, it demonstrates that each transformation stage filters information, and that important defect cues may either be preserved or attenuated depending on the representation strategy.

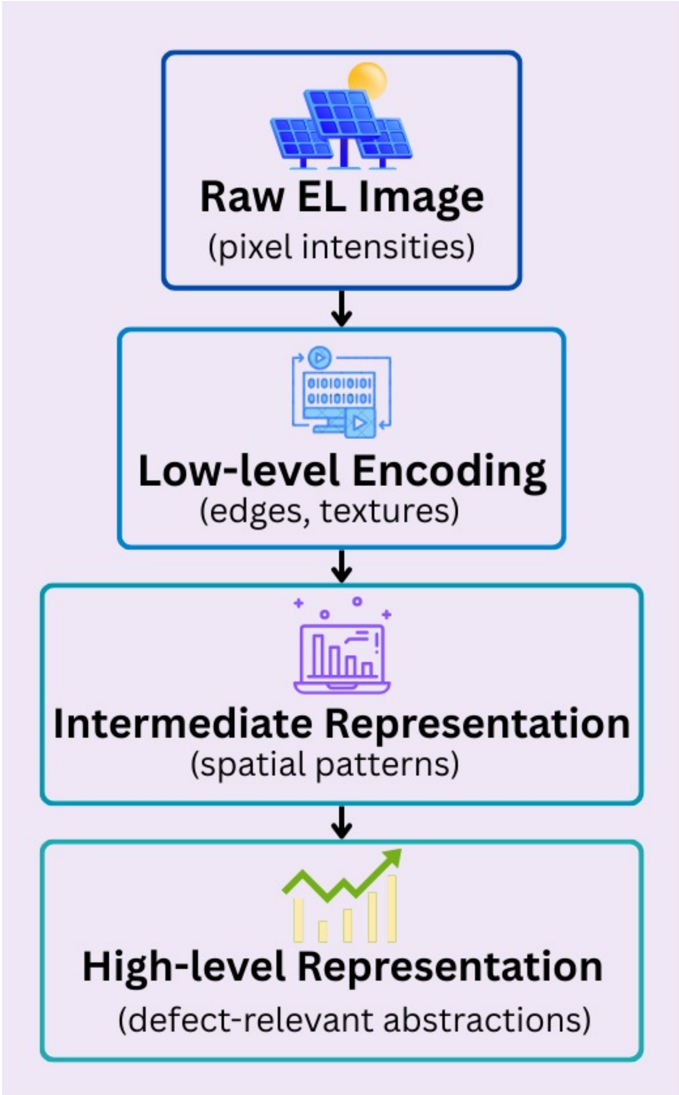

Figure 4. Conceptual illustration of EL image abstraction, showing the transition from raw electroluminescence input to progressively simplified feature representations used for inspection.

4.1 Representation strategies: handcrafted and learned encodings

Foundational studies on EL image analysis assumed that features would reflect basic visual characteristics. Hand crafted features often describe texture, intensity distribution, and edge structure within EL images. For example, gray-level co-occurrence matrix features have been used to quantify spatial texture patterns by measuring contrast, homogeneity, and correlation between neighboring pixel intensities. Such features can help distinguish uniform cell regions from areas disrupted by microcracks or inactive zones, where texture regularity is reduced. Within a controlled context, such representations were often able to differentiate among various defect types, most of the time with some reasonable level of confidence. At the same time, defects elicited a response, and the failures of a defect to manifest predictably were often the result of various conditions. This problem exists in various inspection domains, and is not a phenomenon strictly associated with the imaging of solar cells, yet represents a profound truism of most domains where the design of a representation is a reflection of the prevailing area of knowledge and the conditions of the system in operation [12].

In most cases, more recent methodologies have

Table 2. Relationship between common physical defect categories and their typical visual manifestations in EL images.

Physical defect category	Typical EL manifestation	Visual ambiguity level	Inspection implication
Micro-cracks	Dark linear patterns	High	Risk of misclassification
Shunts	Localized dark spots	Moderate	Requires contextual analysis
Broken fingers	Band-like dim areas	Moderate	Overlaps with cracks
Inactive regions	Diffuse dark zones	High	Hard to localize

favored representations that are learned, more often than not derived from several complex deep neural networks [13]. They might be able to adjust to more subtle differences in EL images, but they might also be encoding correlations that are specific to that dataset. Features that have nothing to do with defect physics could be learned, such as background artifacts or acquisition biases, and that is often hidden in the results.

Several strategies can reduce this risk. Data augmentation techniques, such as controlled variation in brightness, contrast, and noise levels, can expose the model to a broader range of sensing conditions and discourage reliance on fixed background patterns. Domain diversification through multi-site image collection can further limit overfitting to specific acquisition setups. In addition, explainable AI methods such as saliency mapping or gradient-based attribution can be used to verify whether model attention is concentrated on defect regions rather than irrelevant image borders or background artifacts. If attention maps highlight non-defect areas, this signals that the representation may be encoding spurious correlations.

The more transfer learning is used, the more difficult it is to interpret learned representations. Pretrained models are a shortcut to learn faster, but the representations they learn could be built from a different imaging domain. For EL imaging, whether these assumptions are valid depends on the target domain and the data distribution.

4.2 Representation stability and generalization

Representation stability, from a system-level view, is intertwined with generalization. Balanced representation is responsive to meaningful shifts related to the defect, while being unresponsive to the shifts that do not matter. Achieving this is difficult when the data is sparse or diverse. Generalization failures are often linked to the model or training strategy [14]. The representational layer is often ignored. In a sense, representation learning is a filter through which all the subsequent decisions are made. If important information is omitted or deteriorated, all downstream decisions would be made sub-optimally, no matter how advanced the algorithm is. Defect information is encoded and interpreted through learned or handcrafted representations. The recognition of various encoding techniques, their strengths, and shortcomings chronicles inspection performance while also providing the framework for the design of decision strategies, which is the focus of the next part.

Within the proposed inspection framework, the representation layer directly constrains the decision layer. Decisions are made only on the information preserved during encoding. If the representation suppresses subtle contrast variations associated with early-stage defects, the decision module cannot recover that information, regardless of its complexity. Conversely, if irrelevant artifacts are amplified during representation, the decision process may assign confidence to spurious patterns. The choice of encoding strategy, therefore, shapes classification boundaries, confidence calibration, and error asymmetry in downstream inspection outcomes.

5 Decision-making paradigms in automated inspection

Once EL images have been encoded into suitable representations, inspection systems must translate this information into decisions. These decisions may take different forms, ranging from simple accept–reject outcomes to more detailed defect categorization. Although decision-making is often treated as a final step, it plays a central role in determining how inspection results are interpreted and acted upon. In practice, inspection decisions are rarely made in isolation [15]. They are influenced by operational constraints, risk tolerance, and the availability of downstream validation. For this reason, decision-making paradigms should be considered as part of the inspection system rather than as a purely algorithmic output. The decision outcomes

Table 3. Inspection decision outcomes and their associated operational consequences in automated EL-based inspection systems.

Decision outcome	Error type	Operational consequence	Relative cost
False negative	Missed defect	Faulty cell passes inspection	High
False positive	Over-rejection	Unnecessary rejection	Medium
Uncertain case	Deferred decision	Manual review required	Low

and operational consequences are mentioned in Table 3. Relative cost levels are included to illustrate asymmetries between different types of decision errors.

The relative cost levels shown in Table 3 are conceptual and intended to illustrate asymmetric operational consequences rather than to represent quantitative measurements from a specific dataset. Cost is defined here in terms of potential economic impact and reliability risk within a manufacturing context. A false negative is labeled as high cost because a defective cell may proceed to module assembly and contribute to long-term performance degradation. A false positive is assigned a medium cost due to unnecessary rejection or additional inspection effort. An uncertain case requiring manual review is considered lower cost because it introduces delay rather than direct reliability loss. These categories serve as illustrative examples of decision trade-offs within the inspection framework.

5.1 Decision formulations in automated inspection

Many EL-based inspection systems are formulated as classification problems. In this paradigm, images or regions are assigned to predefined defect categories. This approach is straightforward to implement and aligns well with supervised learning frameworks. However, classification assumes that defect classes are clearly separable and that labels are reliably defined. As discussed earlier, these assumptions may not always hold in practice. When visual patterns overlap or when defect severity varies continuously, discrete class assignments may oversimplify the underlying condition of the cell. As a result, classification accuracy alone may not fully reflect inspection quality [16].

Some inspection systems extend beyond image-level classification by identifying defect locations within EL images. Approaches using localization tend to offer boundary-defining feedback. This feedback, in turn, could lead to better outcomes with respect to the inspection process. In manufactured goods, boundary feedback could assist with focused repairs or additional analysis. However, with feedback of this kind, complexity increases. Decisions need to factor in fuzzy boundary determinations and the scale of feedback. In the case of feedback localization errors, the influence of such feedback may be different compared to the case of misclassification, and such differences may elude typical evaluative procedures, yet such differences matter in terms of the utilization of the inspection outcomes [17].

In high-speed manufacturing environments, decision paradigms must align with throughput constraints. Cells often move rapidly along production lines. Image processing time is therefore limited, and decisions are required within strict latency bounds. In these conditions, image-level classification is often preferred over detailed localization because it demands fewer computational resources and supports immediate accept or reject actions. The primary objective in this setting is rapid screening. Localization is more suitable in slower quality control stages or failure analysis workflows. In such environments, the spatial extent of a defect can be examined to guide targeted rework or root cause investigation. This approach yields more detailed diagnostic insight, but the computational burden is increased, and boundary estimation may become ambiguous. The selection between classification and localization is thus shaped by operational priorities, with speed emphasized in high-throughput contexts and detailed corrective assessment emphasized in analytical stages.

The most performed automated inspection processes face the challenge of decision-making under the conditions of boundary ambiguity. In automated inspection systems, boundaries tend to be global, incomplete, or ambiguous. In such systems, confidence metrics play an important role in guiding the feedback to be generated. Instead of forcing a decision to be associated with every input, some systems may be designed to include the option to reject and/or set a threshold for a certain level of uncertainty.

In neural network-based inspection systems, confidence can be derived from the output probability distribution produced by a softmax layer. The maximum predicted class probability is commonly used as a confidence estimate. A threshold can then be defined such that predictions below a predefined probability level are flagged as uncertain rather than automatically classified. For example, if the highest class probability is below 0.75, the system may defer the case for manual review.

More refined approaches involve estimating predictive uncertainty rather than relying solely on softmax probabilities. Techniques such as Monte Carlo dropout during inference or deep ensembles can approximate epistemic uncertainty by evaluating variation across multiple forward passes. Large variance in predictions indicates instability and may trigger a reject decision. Confidence calibration methods, such as temperature scaling, can further improve the reliability of probability estimates before thresholds are applied.

Those cases falling below the confidence criterion may be classified as warranting further inspection. While this may create the impression of a reduction in automated inspection efficiency, it may be the opposite in environments where inspection mistakes may be very costly.

5.2 Aligning decisions with inspection objectives

From a system-level viewpoint, decision-making that aligns with inspection goals and is not optimized just for benchmark metrics is more justifiable. Various use cases may emphasize different goals. In some contexts, defect mitigation may take precedence over alarm reduction. In others, it may be throughput-bottlenecked. This set of priorities indicates that the decision frameworks need to be flexible. A given decision-making policy may not fit all inspection use cases. In this regard, the more flexible one is, the better one can understand the difference in performance of seemingly similar models between different use cases and why evaluation metrics need to be contextualized within the given operational framework. Different decision strategies, be it classification, localization, or confidence, have different assumptions and trade-offs [18]. This articulation also facilitates the examination of the deployment contexts, where the decision impacts become critical [19].

6 Deployment reality: The often-overlooked layer in EL inspection research

The evaluation of research on inspections of solar cells using EL is performed mostly in controlled settings. Datasets are created, conditions of data acquisition are controlled, and performances are evaluated using standardized criteria. These practices are comprehensible. However, they only partially reflect how systems for inspections are expected to function in real-life settings. In manufacturing, systems for inspections are integrated into the workflows of production systems, which offer additional constraints beyond predictive performance. Rapid decision-making is required. Available hardware may be scarce [20]. The results of inspections may be economically and/or socially critically important. These factors indicate that the concept of systems for inspections should be viewed in the context of deployment as a substantive, and perhaps, primary, design consideration.

6.1 Operational and risk constraints

One of the foremost issues with deployments is the time taken for inferences. Inspection systems usually need to deal with high quantities of cells in a time-sensitive manner. Models that would perform well during evaluations may lead to impractical results due to high amounts of required calculations. Many studies that we observe will not contain any mention of inference latency. A practical reporting practice would be to include standardized latency metrics alongside accuracy results. For example, researchers can report average inference time per image and frames processed per second on clearly specified hardware configurations, such as a defined GPU or industrial-grade CPU. Batch size, image resolution, and preprocessing time should also be disclosed. Providing these measurements allows readers to assess whether the proposed model can operate within real-time production constraints rather than only under offline evaluation conditions [21].

Overlooking latency will lead to giving more credit than the study's results can substantiate with regard to the practical use of the model in the field of inspection [22]. The various constraints of deployment behave as a middle layer in the field between the design of the inspection system and its operational behavior [23]. This figure illustrates how various deployment factors limit and shape the behavior of the system as a reminder that high accuracy is not the only required factor. A conceptual illustration of deployment constraints influencing EL-based solar cell inspection systems is shown in Figure 5.

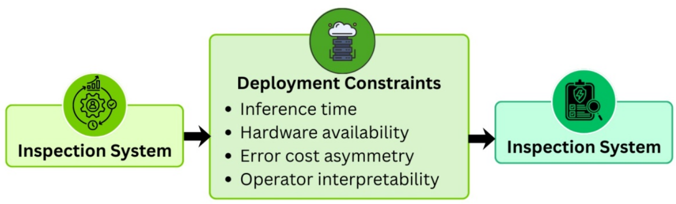

Figure 5. Conceptual illustration of deployment constraints influencing EL-based solar cell inspection systems.

Figure 5 presents deployment as a constraining layer that surrounds the inspection system. Hardware capacity limits model size and inference speed. Latency requirements reduce allowable processing complexity. Economic risk shapes acceptable error rates, especially for false negatives. Workflow integration determines whether outputs can be acted upon in real time. These factors collectively influence system behavior beyond accuracy metrics.

Different mistakes in inspections can result in different consequences. In an industry, risks associated with true negatives and true positives differ. A defect that is missed can cause issues in the future, and module reliability can be impacted. Instantly rejecting or putting too much work into something because of an unnecessary defect can also cause issues. Regardless of this, most research continues to use accuracy metrics that disregard the magnitude of each mistake. These metrics can be used for benchmarking, but they do not explain the risk associated with the inspection. Evaluations that consider constraining deployments gain value from being more sophisticated, where types of mistakes are examined against operational goals.

6.2 Human and environmental factors

Use of automated inspection systems is seldom in complete isolation. Altogether, humans need to review these outputs, especially when the outcomes are uncertain or costly. This explains why, in practical terms, the system needs to be deployable. Trust and troubleshoot are easier to gain when systems explain the rationale driving their actions. From an operational standpoint, the ability to predict outcomes is not enough to automate systems. This response indicates that operational inspection systems are automated based on the efficiency of the human system, not on the algorithm. Automation is consistent with the unique demands present in the deployment environment. Hardware, environment, and the system in which task performance occurs can all shift in terms of the data that needs processing. Systems operate poorly when trained on datasets that are not representative of the actual data.

Though the ability to maintain steady processing performance in the face of variability is usually desired, it is unclear what that means in the context of inspection systems. It involves paradoxical design choices that favor steady performance and limit variability over design choices that favor peak performance. Factors like speed; cost of mistakes, how understandable they are, and variability all impact how the results of inspections are used in the real world. When these factors are ignored, the practical use of the results and conclusions from the research becomes challenging. This leads to a need for reflection on the prevailing research practices, which will be discussed in the next section [24].

7 Research blind spots and misaligned evaluation practices

Although there has been great interest in researching EL-based solar cell inspection, there has also been research in different fields of study that have been of greater interest when looking at models of solar cell data. As research continues, there are models that EL-based solar cell inspection may be able to adapt to overcome, assuming that these models are viewed more as an opportunity than a barrier. One of these models includes the composition of the data. Studies that have examined the use of EL-based solar cell technology have been performed in less-than-ideal situations using data, instances, and variables that are very similar and that have been collected under conditions that do not have a lot of diversity [25]. Because of this, there may be an optimum level of data that may be underutilized. Figure 6 examines the methods of data collection in an academic world from an industrial world without taking a critical approach to the studies that have been performed.

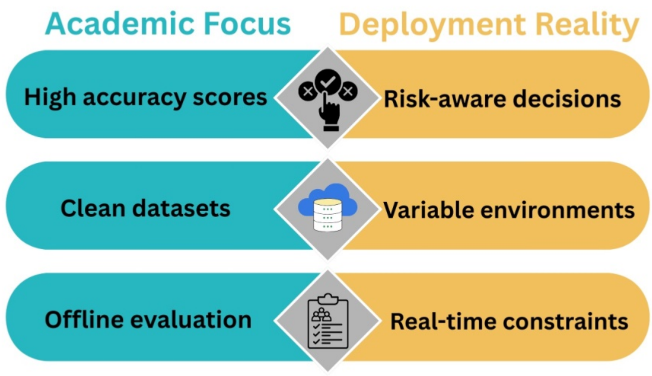

Figure 6. Conceptual comparison between academic evaluation focus and deployment reality in EL-based solar cell inspection.

Figure 6 contrasts two perspectives. On the academic side, emphasis is placed on benchmark accuracy, controlled datasets, and offline evaluation. On the industrial side, priorities shift toward reliability under variability, latency constraints, economic risk, and integration into production workflows. The comparison highlights the gap between experimental validation and operational performance expectations.

An additional consideration has to do with metrics for evaluation. While there may be discussions on measuring methods and metrics available, less attention is given to the limitations of the various measures, including accuracy and all related measures. Measures used for evaluation that center on ease of

Table 4. Comparison between commonly adopted evaluation practices and their potential limitations.

Evaluation practice	Common rationale	Deployment mismatch	Suggested alternative practice
Accuracy based metrics	Easy comparison	Ignores error costs	Use cost sensitive metrics such as weighted loss or risk adjusted evaluation
Clean datasets	Controlled experiments	Fails under variability	Include multi source datasets with sensing variability and domain shift
Offline evaluation	Reproducibility	Not real time feasible	Report inference latency and throughput on specified hardware

use may not capture critical features of the quality of the inspection. While the repetitive nature of these observations across studies might suggest that evaluation has become routine, in many instances, the evaluative framework does not sufficiently capture the goal of the inspection. There is the partitioning of algorithmic versus operational 'siloing.' It is well understood that operational limitations create constraints, but these are rarely examined.

One practical mechanism to reduce this divide is the creation of shared industry academia benchmark datasets. These datasets would combine controlled laboratory images with data captured under real manufacturing variability. Detailed documentation of acquisition hardware, illumination settings, defect annotation procedures, and operational context should be provided. Such transparency is essential. When heterogeneous and deployment representative data are made available, models can be evaluated under realistic sensing and environmental conditions instead of relying only on curated laboratory samples. Evaluation practices are then grounded in operational realities. This shift encourages alignment between academic research and industrial constraints.

The recurring issues of deployment, selection of metrics, and the bias in research appear in all systems [21]. They most likely represent more significant constraints on the research system. Such constraints indicate the need for a system-wide perspective that outlines the next set of research priorities. It highlights instances where the experimental conditions are likely not to meet the operational conditions.

Table 4 proposes corrective practices. Cost-sensitive evaluation aligns metrics with economic risk. Inclusion of heterogeneous datasets improves robustness to sensing variability. Reporting latency and throughput ensures feasibility under real-time production constraints. These alternatives shift evaluation from algorithm-centric benchmarking toward deployment-aware assessment.

8 Future directions through a system-level lens

Previous sections examined the limitations of treating electroluminescence inspection as an isolated modeling problem. Future research should therefore adopt a system-level perspective that considers interactions between physical mechanisms, sensing variability, representation design, decision strategies, and deployment constraints. The directions outlined in this section focus on strengthening these interconnections rather than introducing isolated algorithmic improvements. Figure 7 summarizes these priorities within the proposed framework.

Figure 7 highlights four interconnected future directions. First, tighter integration between physical defect modeling and data driven learning is proposed to reduce semantic ambiguity and improve interpretability. Second, adaptive inspection systems capable of responding to shifts in sensing conditions and manufacturing environments are emphasized. Third, deployment aligned evaluation practices are recommended, including cost sensitive metrics and latency reporting. Fourth, human supported decision frameworks are encouraged, where automated systems assist rather than fully replace expert inspection in high risk scenarios.

8.1 System integration and adaptability

Physical defect mechanisms and data-driven analysis are often handled separately in machine learning defect detection in the literature. For example, while machine learning models can identify visual patterns, they might detect a defect without having a perceptive understanding of the defect. Closing this gap could improve interpretability and reliability across different conditions.

One specific research direction is the development of physics informed neural networks for electroluminescence inspection. In such an approach,

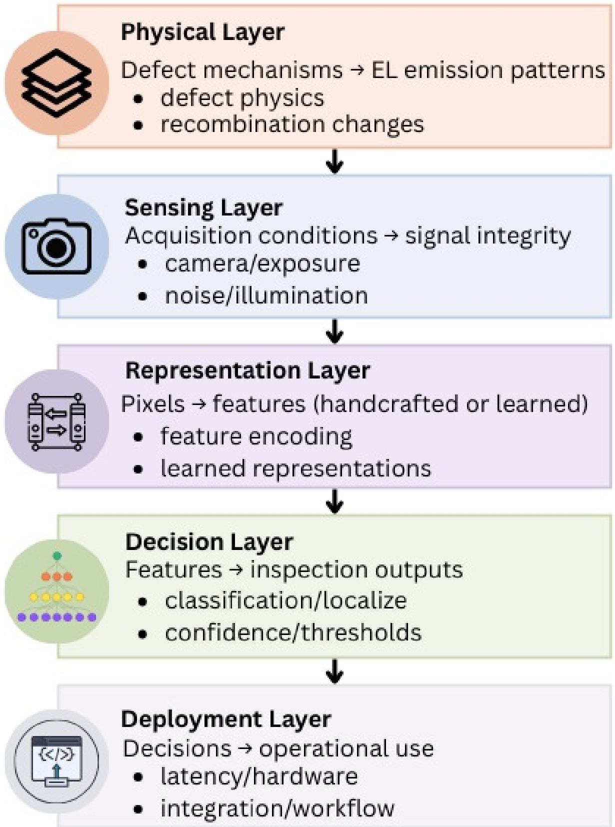

Figure 7. System-level future directions for EL-based solar cell inspection.

the neural network would be trained not only on labeled EL images but also constrained by simplified electrical models of carrier recombination and current flow. For example, predicted defect regions could be regularized to align with physically plausible current interruption patterns or continuity constraints derived from cell structure. Loss functions may incorporate penalties when predicted defect maps contradict known electrical behavior, such as unrealistic discontinuities in current pathways. This integration would encourage the learned representation to remain consistent with defect physics rather than relying solely on statistical correlations.

Further work could imagine inspection pipelines that embody more physical boundary constraints and incorporate more domain craft. Perhaps more minimal modeling that embodies the constraints more fully, relative to the learned representation, could result in fewer spurious correlations and improved inspection outcomes. The literature has described modeling environments as having a fixed boundary and stable configuration. In practice, this is not the case with inspection environments. Gradual changes to equipment, shifts in production, and moving environmental factors can alter the inspection processes. These changes can lead to unaccounted-for shifts in boundary conditions. Volume in this case is not an exception, and more order, fewer problem-solving approaches are likely to provide more resilient inspection processes. This aligns with the literature, which notes that inspection systems are not static in their operational functionality. Instead, systems seem to lose their operational utility over time because of changes in the processes to which they are used.

Another line of thinking involves re-evaluating the purpose of automation. In some cases, the goal may not be the complete removal of human inspections, but rather the augmentation of human inspections. For example, systems that support human operators by drawing their focus to certain areas or indicating areas of gray uncertainty may be more accepted than systems that mandate decisions without human involvement. This change of focus still keeps the need for algorithms to be accurate; however, it signifies that accuracy is but one part of a larger decision support system.

8.2 Evaluation practices aligned with operational goals

Future progress in EL-based inspection also depends on how systems are evaluated. Metrics that are simply quantifiable and easy to report will not always be the most informative for deployment. There is scope for greater alignment between evaluation practices and operational objectives, such as risk tolerance, throughput, and maintenance constraints. Designing evaluation protocols that reflect these priorities will likely require a greater degree of collaboration between researchers and industry practitioners. While such collaboration may be challenging, it is likely to be most useful for determining what is most important in practice in terms of system performance. Rather than concentrating on several disparate methodological advancements, these directions focus on system integration, system flexibility, and alignment with actual inspection requirements. Collectively, these factors indicate that for more comprehensive advancements to occur, inspection systems must be properly positioned within their physical and operational environments.

One possible direction is the introduction of a multi-objective inspection benchmark that evaluates models along three coordinated dimensions: predictive reliability, computational efficiency, and interpretability. Predictive reliability could be assessed using cost-sensitive accuracy or weighted risk metrics that penalize false negatives more heavily than false positives. Computational efficiency should be reported as average inference time per image and frames processed per second on standardized hardware configurations. Interpretability may be evaluated through localization agreement scores or expert-rated relevance of explanation maps, measuring whether highlighted regions correspond to physically meaningful defect areas.

A composite inspection performance index could then be computed as a weighted aggregation of these dimensions, with weights defined according to deployment priorities. Such a benchmark would discourage models that optimize accuracy at the expense of latency or transparency and would align evaluation with real inspection objectives.

From a system-level perspective, three directions emerge as particularly important.

1. *Physics-informed inspection models*
   Future research should integrate simplified electrical and structural constraints directly into learning frameworks. Embedding physical consistency within neural networks can reduce semantic ambiguity and improve generalization under sensing variability.

2. *Deployment-aligned evaluation benchmarks*
   Accuracy alone is insufficient. Evaluation protocols should jointly report cost-sensitive reliability, inference latency on standardized hardware, and explanation consistency. Multi-objective benchmarks would better reflect operational inspection requirements.

3. *Shared industry academia datasets with real variability*
   Publicly available datasets that combine laboratory-controlled images with real manufacturing variability would reduce research siloing. Transparent documentation of hardware, illumination, and annotation protocols would enable realistic cross-study comparison.

9 Conclusion

This study examined electroluminescence-based solar cell inspection through a five-layer system framework. A layer-specific analysis was conducted to identify structural limitations often overlooked in model-centered research. At the physical layer, defect visibility was shown to depend on underlying electrical behavior, which places inherent limits on detectability regardless of algorithm choice. Not all defects produce a strong contrast. At the sensing layer, acquisition variability was identified as a significant source of inconsistency across datasets, and inspection performance was found to be sensitive to exposure conditions, hardware settings, and noise. Within the representation layer, encoding strategies were shown to determine which defect cues are preserved and which are suppressed. Decisions are constrained by these representations. At the decision layer, error asymmetry and uncertainty management were highlighted as central to inspection reliability, particularly in manufacturing contexts where false negatives carry greater operational risk. Confidence-based rejection strategies were discussed as a mechanism to balance automation with caution. The deployment layer revealed additional constraints. Latency requirements, hardware limitations, and workflow integration were shown to shape system feasibility beyond predictive accuracy. Even high-performing models may fail under real production conditions. A system-oriented perspective is therefore required. Future progress will depend on aligning physical insight, representation design, decision strategy, and deployment realities within a unified inspection framework.

Data Availability Statement

Not applicable.

Funding

This work was supported without any funding.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Khan, A., Sohail, A., Zahoora, U., & Qureshi, A. S. (2020). A survey of the recent architectures of deep

convolutional neural networks. *Artificial Intelligence Review, 53*(8), 5455–5516. [CrossRef]

[2] Al-Mashhadani, R., Alkawsi, G., Baashar, Y., Alkahtani, A. A., Nordin, F. H., Hashim, W., & Kiong, T. S. Deep Learning Methods for Solar Fault Detection and Classification: A Review. *solar cells, 11*, 12. [CrossRef]

[3] Al-Otum, H. M. (2023). Deep learning-based automated defect classification in electroluminescence images of solar panels. *Advanced Engineering Informatics, 58*, 102147. [CrossRef]

[4] Al-Otum, H. M. (2026). Defect classification of photovoltaic solar cells using electroluminescence imaging and enhanced deep learning approaches. *Solar Energy, 303*, 114085. [CrossRef]

[5] Shahbazi, N., Lin, Y., Asudeh, A., & Jagadish, H. V. (2023). Representation Bias in Data: A Survey on Identification and Resolution Techniques. *ACM Computing Surveys, 55*(13s), 1–39. [CrossRef]

[6] Kausik, A. K., Rashid, A. B., Baki, R. F., & Jannat Maktum, M. M. (2025). Machine learning algorithms for manufacturing quality assurance: A systematic review of performance metrics and applications. *Array, 26*, 100393. [CrossRef]

[7] Abdelsattar, M., Abdelmoety, A., Ismeil, M. A., & Emad-Eldeen, A. (2025). Automated defect detection in solar cell images using deep learning algorithms. *IEEE Access, 13*, 4136-4157. [CrossRef]

[8] Ahan, M. R., Nambi, A., Ganu, T., Nahata, D., & Kalyanaraman, S. (2021, November). AI-assisted cell-level fault detection and localization in solar PV electroluminescence images. In *Proceedings of the 19th ACM conference on embedded networked sensor systems* (pp. 485-491). [CrossRef]

[9] Puranik, V. E., Kumar, R., & Gupta, R. (2023). Progress in module level quantitative electroluminescence imaging of crystalline silicon PV module: A review. *Solar Energy, 264*, 111994. [CrossRef]

[10] Frisch, M., Baumgärtner, J., Heider, I., Puchta, A., & Fleischer, J. (2024). Efficient Deployment of Machine Learning Models in Manufacturing and Industrial Environments using ROS. *Procedia CIRP, 130*, 188–193. [CrossRef]

[11] Xia, B., Li, S., Li, N., Li, H., & Tian, X. (2023). Surface defect recognition of solar panel based on percolation-based image processing and serre standard model. *IEEE Access, 11*, 55126–55138. [CrossRef]

[12] Tang, W., Yang, Q., Xiong, K., & Yan, W. (2020). Deep learning based automatic defect identification of photovoltaic module using electroluminescence images. *Solar Energy, 201*, 453-460. [CrossRef]

[13] Sun, M., Lv, S., Zhao, X., Li, R., Zhang, W., & Zhang, X. (2017, August). Defect detection of photovoltaic modules based on convolutional neural network. *In International Conference on Machine Learning and Intelligent Communications* (pp. 122-132). Cham: Springer International Publishing. [CrossRef]

[14] Wang, C., Chen, H., & Zhao, S. (2023). RERN: Rich edge features refinement detection network for polycrystalline solar cell defect segmentation. *IEEE Transactions on Industrial Informatics, 20*(2), 1408-1419. [CrossRef]

[15] Lee, I. B., Kim, Y., & Kim, S. (2025). A Data-Driven Machine Vision Framework for Quality Management in Photovoltaic Module Manufacturing. *Machines, 13*(4), 285. [CrossRef]

[16] Drir, N., Mellit, A., Blasuttigh, N., & Pavan, A. M. (2026). Enhancing defect detection in photovoltaic cells through advanced cascade CNN with attention mechanisms on electroluminescence images. *Energy Conversion and Management, 348*, 120636. [CrossRef]

[17] Balzategui, J., Eciolaza, L., & Maestro-Watson, D. (2021). Anomaly detection and automatic labeling for solar cell quality inspection based on generative adversarial network. *Sensors, 21*(13), 4361. [CrossRef]

[18] Rodriguez, A., Gonzalez, C., Fernandez, A., Rodriguez, F., Delgado, T., & Bellman, M. (2021). Automatic solar cell diagnosis and treatment. *Journal of Intelligent Manufacturing, 32*(4), 1163–1172. [CrossRef]

[19] Masita, K., Hasan, A., Shongwe, T., & Hilal, H. A. (2025). Deep learning in defects detection of PV modules: A review. *Solar Energy Advances, 5*, 100090. [CrossRef]

[20] Hussain, T., Hussain, M., Al-Aqrabi, H., Alsboui, T., & Hill, R. (2023). A review on defect detection of electroluminescence-based photovoltaic cell surface images using computer vision. *Energies, 16*(10), 4012. [CrossRef]

[21] Paleyes, A., Urma, R. G., & Lawrence, N. D. (2022). Challenges in deploying machine learning: a survey of case studies. *ACM computing surveys, 55*(6), 1-29. [CrossRef]

[22] Zheng, J., Lv, F., Ding, Y., Guo, C., Wang, Y., Yi, D., ... & Sun, X. (2026). Physics-informed deep learning for surface defect detection on optical wedge plates: enhancing accuracy and generalization. *Journal of Intelligent Manufacturing*, 1-15. [CrossRef]

[23] Ebied, M. A., Munshi, A., Alhuzali, S. A., El-Sotouhy, M. M., Shehta, A. I., & Elborlsy, M. S. (2025). Advanced deep learning modeling to enhance detection of defective photovoltaic cells in electroluminescence images. *Scientific Reports, 15*(1), 31640. [CrossRef]

[24] Sezen, B., & Cerasi, C. C. (2023). Solar cell busbars surface defect detection based on deep convolutional neural network. *IEEE Latin America Transactions, 21*(2), 242-250. [CrossRef]

[25] Chen, H., Pang, Y., Hu, Q., & Liu, K. (2020). Solar cell surface defect inspection based on multispectral convolutional neural network. *Journal of Intelligent Manufacturing, 31*(2), 453-468. [CrossRef]

Rehana Ghulam is a committed researcher specializing in artificial intelligence, healthcare analytics, and Internet of Things (IoT) environments. Her expertise spans machine and deep learning applications in medical diagnosis, speech recognition, and facial emotion analysis. She has contributed to several IoT-driven projects, including malware detection, anomaly identification, and cyberattack prediction. Rehana is deeply passionate about creating AI-based solutions for early disease detection and enhancing patient outcomes. She actively engages in interdisciplinary research, working with both clinical records and image-based medical data. (Email: rehanaghulam97@gmail.com)

Muhammad Fahad Amin Ramay is a dedicated researcher specializing in Artificial Intelligence and Data Science, with a strong focus on machine learning and deep learning methodologies. His research interests include intelligent data-driven modeling, predictive analytics, speech and signal processing, and pattern recognition. He has worked on multiple AI-based projects involving large-scale data analysis, classification, and decision-support systems. Muhammad Fahad Amin Ramay is particularly passionate about developing robust and scalable AI models for real-world applications and actively engages in interdisciplinary research leveraging structured, unstructured, and high-dimensional datasets. (Email: Fahad.ramey@gmail.com)

Aiza Mukhtar is a dedicated researcher specializing in AI, healthcare analytics, and IoT-based systems. Her work focuses on leveraging machine learning and deep learning for medical diagnostics and cybersecurity. Passionate about innovation, she aims to develop intelligent tools for early disease detection and improved healthcare. (Email: misaizarao1122@gmail.com)

Kainat is a dedicated researcher specializing in Artificial Intelligence and data-driven systems. Her work focuses on applying machine learning and deep learning techniques to intelligent analytics and real-world problem solving. She is passionate about developing innovative AI solutions that enhance decision-making and system efficiency. (Email: kainatarshad262@gmail.com)

Saba Farid is a researcher specializing in Artificial Intelligence, healthcare analytics, and IoT-based systems. Her work focuses on machine learning and deep learning for early disease detection and securing medical systems. (Email: Sabafareed2512@gmail.com)

Nikhat Fatima is an aspiring AI Researcher pursuing at Kakatiya University, Hanamkonda, with specialized interest in machine learning, neural networks, and intelligent systems. Her research focuses on developing innovative AI solutions to address real-world challenges through computational intelligence and data-driven approaches. (Email: nikhat.zbr@gmail.com)

Khaleelullah Syed is an AI Researcher and Computer/Information Technology Services Administration professional from Hellenic American University, specializing in artificial intelligence, machine learning applications, and IT infrastructure management. His work bridges cutting-edge AI research with practical technology administration, developing intelligent systems that enhance organizational efficiency and decision-making. (Email: ksyed@hauniv.edu)